

SELECTING GOOD EXPONENTIAL POPULATIONS
COMPARED WITH A CONTROL:
A NONPARAMETRIC EMPIRICAL BAYES APPROACH*

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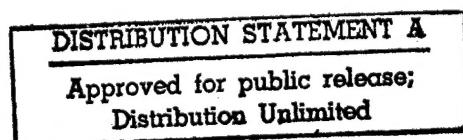
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Abstract

This paper deals with empirical Bayes selection procedures for selecting good exponential populations compared with a control. Based on the accumulated historical data, an empirical Bayes selection procedure δ_n^* is constructed by mimicking the behavior of a Bayes selection procedure. The empirical Bayes selection procedure δ_n^* is proved to be asymptotically optimal. The analysis shows that the rate of convergence of δ_n^* is influenced by the tail probabilities of the underlying distributions. It is shown that under certain regularity conditions on the moments of the prior distribution, the empirical Bayes selection procedure δ_n^* is asymptotically optimal of order $O(n^{-\lambda/2})$ for some $0 < \lambda \leq 2$. A lower bound with rate of convergence of order $O(n^{-1})$ is also established for the regret Bayes risk of the empirical Bayes selection procedure δ_n^* . This result suggests that a rate of order $O(n^{-1})$ might be the best possible rate of convergence for this empirical Bayes selection problem.

Short Title: Empirical Bayes Selection for Exponential Populations

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1. Introduction

The exponential distribution has played an important role for modeling the life time distribution of a variety of random phenomena. This distribution arises in many areas of applications, including reliability, life-testing and survival analysis. An overall introduction and more applications of the exponential distribution model can be seen, for example, in the contents of Johnson, Kotz and Balakrishnan (1994) and Balakrishnan and Basu (1995).

Consider k independent exponential populations π_1, \dots, π_k , with associated population means $\theta_i, i = 1, \dots, k$, respectively. The θ_i 's are unknown. Let θ_0 be a specified standard. Population π_i is said to be good if $\theta_i \geq \theta_0$, and bad otherwise. In many practical situations, an experimenter is often confronted with the problem of comparing the k alternatives with the specified standard θ_0 , and selecting the more promising subset of the k populations for further experimentation. The problem is known as comparison with a control problem. A review of subset selection procedures in this context is contained in Gupta and Panchapakesan (1985).

Now, consider a situation in which one is repeatedly dealing with the same selection problem independently. In such instances, it is reasonable to formulate the component problem in the sequence as a Bayes decision problem with respect to an unknown prior distribution on the parameter space. One then draws useful information from the accumulated historical data to improve the decision at each stage. This is the empirical Bayes approach due to Robbins (1956, 1964). Empirical Bayes procedures have been derived for subset selection goals by Deely (1965). Recently, Gupta and Liang (1988, 1994) and Gupta, Liang and Rau (1994a, 1994b) have studied certain selection problems using the empirical Bayes approach. Many such empirical Bayes procedures have been shown to be asymptotically optimal in the sense that the Bayes risk for the $(n+1)$ -st decision problem converges to the optimal Bayes risk which would have been obtained if the prior distributions were fully known and the Bayes procedure with respect to this prior distribution were used.

In this paper, we are dealing with the problem of selecting good exponential populations compared with a control using the empirical Bayes approach. In Section 2, the selection problem is formulated and a Bayes selection procedure is derived. In Section

3, an empirical Bayes selection procedure δ_n^* is constructed by mimicking the behavior of the Bayes selection procedure. The asymptotic optimality of the empirical Bayes selection procedure is established in Section 4. The associated rate of convergence of the regret Bayes risk of δ_n^* is also investigated. The analysis shows that the rate of convergence is influenced by the tail probabilities of the underlying distributions. It is shown that under certain regularity conditions about the moments of the prior distribution, the empirical Bayes selection procedure δ_n^* is asymptotically optimal of order $O(n^{-\lambda/2})$ for some $0 < \lambda \leq 2$. A lower bound with rate of convergence of order $O(n^{-1})$ is also established for the regret Bayes risk of the empirical Bayes selection procedure δ_n^* . This result suggests that a rate of order $O(n^{-1})$ might be the best possible rate of convergence for the empirical Bayes selection problem.

2. Formulation of the Selection Problem

Consider k independent exponential populations π_1, \dots, π_k , with probability density function $h_i(x_i|\theta_i) = \frac{1}{\theta_i} e^{-x_i/\theta_i}$, $x_i > 0, \theta_i > 0$, respectively. The θ_i 's, $i = 1, \dots, k$, are unknown. For a specified standard $\theta_0 > 0$, population π_i is said to be good if $\theta_i \geq \theta_0$, and bad otherwise. The selection goal is to select all good populations and to exclude all bad populations.

Let $\Omega = \{\underline{\theta} = (\theta_1, \dots, \theta_k) | \theta_i > 0, i = 1, \dots, k\}$ be the parameter space and let $\mathcal{A} = \{\underline{a} = (a_1, \dots, a_k) | a_i = 0, 1; i = 1, \dots, k\}$ be the action space. When an action \underline{a} is taken, it means that population π_i is selected as good if $a_i = 1$, and excluded as bad if $a_i = 0$. For parameter $\underline{\theta}$ and action \underline{a} , the loss function $L(\underline{\theta}, \underline{a})$ is defined as:

$$L(\underline{\theta}, \underline{a}) = \sum_{i=1}^k \ell(\theta_i, a_i) \quad (2.1)$$

where

$$\ell(\theta_i, a_i) = a_i \theta_i (\theta_0 - \theta_i) I(\theta_0 > \theta_i) + (1 - a_i) \theta_i (\theta_i - \theta_0) I(\theta_i \geq \theta_0) \quad (2.2)$$

and $I(A)$ is the indicator function of the event A .

For each $i = 1, \dots, k$, let X_{i1}, \dots, X_{im} be a sample of size m arising from population π_i with probability density $h_i(x|\theta_i)$. Let $Y_i = \sum_{j=1}^m X_{ij}$. Then Y_i follows a gamma distribution with probability density $f_i(y|\theta_i) = \frac{y^{m-1}}{\Gamma(m)\theta_i^m} e^{-y/\theta_i}$. Note that Y_i is a sufficient statistic

for the parameter θ_i . Since the Bayes and empirical Bayes approaches will be employed, it suffices to deal with the sufficient statistics Y_1, \dots, Y_k . It is assumed that for each $i = 1, \dots, k$, the parameter θ_i is a realization of a random parameter Θ_i with an unknown prior distribution on G_i on θ_i over $(0, \infty)$, and $\Theta_1, \dots, \Theta_k$ are mutually independent. It is also assumed that $G_i, i = 1, \dots, k$, are non-degenerate and satisfy that $\int \theta^2 dG_i(\theta) < \infty$ to insure the Bayes risk to be finite and this selection problem to be meaningful. We let $G(\underline{\theta}) = \prod_{i=1}^k G_i(\theta_i)$.

Let $\underline{Y} = (Y_1, \dots, Y_k)$ and \mathcal{Y} denote the sample space of \underline{Y} . A selection procedure $\underline{\delta} = (\delta_1, \dots, \delta_k)$ is defined to be a measurable mapping from the sample space \mathcal{Y} into the product space $[0, 1]^k$, so that for each $y \in \mathcal{Y}$, $\underline{\delta}(y) = (\delta_1(y), \dots, \delta_k(y))$ and $\delta_i(y)$ is the probability of selecting population π_i as good. Let \mathcal{C} be the class of all selection procedures. For each $\underline{\delta} \in \mathcal{C}$, let $R(G, \underline{\delta})$ denote its associated Bayes risk. Then, $R(G) = \inf_{\underline{\delta} \in \mathcal{C}} R(G, \underline{\delta})$ is the minimum Bayes risk among the class \mathcal{C} . A selection procedure $\underline{\delta}_G$ satisfying $R(G, \underline{\delta}_G) = R(G)$ is called a Bayes selection procedure. Note that $R(G) < \infty$ under the assumption that $\int \theta^2 dG_i(\theta) < \infty, i = 1, \dots, k$.

Let $c(\theta) = (\Gamma(m)\theta^m)^{-1}, u(y) = y^{m-1}$. Then $f_i(y|\theta_i) = c(\theta_i)u(y)e^{-y/\theta_i}$. Let $f(y|\underline{\theta}) = \prod_{i=1}^k f_i(y|\theta_i)$. Also, for each $i = 1, \dots, k, y > 0$ and nonnegative integer a , define

$$\psi_{ia}(y) = \int_{\theta=0}^{\infty} \theta^a c(\theta) e^{-y/\theta} dG_i(\theta). \quad (2.3)$$

Then, $f_i(y) = \int f_i(y|\theta) dG_i(\theta) = u(y)\psi_{i0}(y)$ is the marginal probability density of Y_i . Let $f(y) = \prod_{i=1}^k f_i(y_i)$.

From the preceding statistical model and the loss function $L(\underline{\theta}, \underline{a})$, the Bayes risk associated with the selection procedure $\underline{\delta}$ is:

$$R(G, \underline{\delta}) = \sum_{i=1}^k R_i(G, \delta_i) \quad (2.4)$$

and

$$\begin{aligned} R_i(G, \delta_i) &= \int \left[\left[\prod_{\substack{j=1 \\ j \neq i}}^k f_j(y_j) \right] u(y_i) \delta_i(y) [\theta_0 \psi_{i1}(y_i) - \psi_{i2}(y_i)] dy + C_i \right. \\ &= \int \left[\left[\prod_{\substack{j=1 \\ j \neq i}}^k f_j(y_j) \right] u(y_i) \delta_i(y) \psi_{i1}(y_i) [\theta_0 - \varphi_i(y_i)] dy + C_i, \end{aligned} \quad (2.5)$$

where $C_i = \int_{\Omega} \theta_i(\theta_i - \theta_0)I(\theta_i > \theta_0)dG(\theta)$ which is independent of the selection procedure δ , and $\varphi_i(y_i) = \frac{\psi_{i2}(y_i)}{\psi_{i1}(y_i)}$.

Let $H_i(y_i) = \theta_0\psi_{i1}(y_i) - \psi_{i2}(y_i) = \psi_{i1}(y_i)[\theta_0 - \varphi_i(y_i)]$. Note that $\psi_{i1}(y_i) > 0$. From (2.5), a Bayes selection procedure $\delta_G = (\delta_{G1}, \dots, \delta_{Gk})$ can be obtained as follows: For each $y \in \mathcal{Y}$ and $i = 1, \dots, k$,

$$\begin{aligned} \delta_{Gi}(y) &= \begin{cases} 1 & \text{if } H_i(y_i) \leq 0, \\ 0 & \text{otherwise,} \end{cases} \\ &= \begin{cases} 1 & \text{if } \varphi_i(y_i) \geq \theta_0, \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \quad (2.6)$$

Note that for each component i , δ_{Gi} depends on y only through y_i . Therefore $\delta_{Gi}(y)$ can be written as $\delta_{Gi}(y_i)$. The minimum Bayes risk is

$$R(G, \delta_G) = \sum_{i=1}^k R_i(G, \delta_{Gi}) \quad (2.7)$$

and

$$\begin{aligned} R_i(G, \delta_{Gi}) &= \int_{y=0}^{\infty} u(y)\delta_{Gi}(y)\psi_{i1}(y)[\theta_0 - \varphi_i(y)]dy + C_i \\ &= \int_{y=0}^{\infty} u(y)\delta_{Gi}(y)H_i(y)dy + C_i. \end{aligned} \quad (2.8)$$

Note that $\varphi_i(y) = \frac{\int \theta^2 c(\theta) e^{-y/\theta} dG_i(\theta)}{\int \theta c(\theta) e^{-y/\theta} dG_i(\theta)}$ is continuous and strictly increasing in y since the prior distribution G_i is non-degenerate. We assume

Assumption A $\lim_{y \rightarrow 0} \varphi_i(y) < \theta_0 < \lim_{y \rightarrow \infty} \varphi_i(y), i = 1, \dots, k$.

Under Assumption A, for each $i = 1, \dots, k$, there exists a unique value $a_i \equiv a_i(\theta_0)$ such that $\varphi_i(a_i) = \theta_0, \varphi_i(y) < \theta_0$ if $y < a_i, \varphi_i(y) > \theta_0$ if $y > a_i$. Hence, the Bayes selection procedure $\delta_G = (\delta_{G1}, \dots, \delta_{Gk})$ can be represented as: For each $i = 1, \dots, k$ and $y > 0$

$$\delta_{Gi}(y) = \begin{cases} 1 & \text{if } y \geq a_i, \\ 0 & \text{otherwise.} \end{cases} \quad (2.9)$$

Finally, for each $i = 1, \dots, k$, let $dG_i^*(\theta) = \frac{\theta dG_i(\theta)}{m_1(G_i)}$, where $m_1(G_i) = \int \theta dG_i(\theta)$. Then, G_i^* is also a distribution on θ_i over $(0, \infty)$. Define

$$f_i^*(y) = \int f_i(y|\theta) dG_i^*(\theta) = u(y)\psi_{i1}(y)/m_1(G_i). \quad (2.10)$$

Then, $\varphi_i(y) = \frac{\psi_{i2}(y)}{\psi_{i1}(y)} = E_{G_i^*}[\Theta_i|Y_i = y]$: the "posterior mean" of Θ_i given $Y_i = y$ and G_i^* is the prior distribution of Θ_i . Hence, $R_i(G, \delta_{G_i})$ can be represented as:

$$R_i(G, \delta_{G_i}) = \int_{y=0}^{\infty} m_1(G_i) f_i^*(y) \delta_{G_i}(y) [\theta_0 - \varphi_i(y)] dy + C_i. \quad (2.11)$$

Note that the Bayes selection procedure δ_G depends on the prior distribution G . Since G is unknown, it is not possible to implement the Bayes selection procedure δ_G for the selection problem at hand. In the following, the empirical Bayes approach is employed.

3. Construction of An Empirical Bayes Selection Procedure

3.1 Empirical Bayes Framework

The empirical Bayes framework of the selection problem is given as follows.

For each $i = 1, \dots, k$, at stage ℓ , let $(Y_{i\ell}, \Theta_{i\ell})$ denote a pair of random vector so that $Y_{i\ell}$ is observable, but $\Theta_{i\ell}$ is not observable. Also, given $\Theta_{i\ell} = \theta_{i\ell}$, $Y_{i\ell}$ follows as a gamma distribution with probability density $f_i(y|\theta_{i\ell})$ and $\Theta_{i\ell}$ has a prior distribution G_i . It is assumed that $(Y_{i\ell}, \Theta_{i\ell}), i = 1, \dots, k; \ell = 1, 2, \dots$ are mutually independent. At the present stage $n + 1$, we let $\underline{Y}_i(n) = (Y_{i1}, \dots, Y_{in})$ denote the historical data and $Y_i = Y_{i,n+1}$ the present random observation associated with population $\pi_i, i = 1, \dots, k$. Let $\underline{Y}(n) = (\underline{Y}_1(n), \dots, \underline{Y}_k(n))$ and $\underline{Y} = (Y_1, \dots, Y_k)$. At the present stage $n + 1$, we consider the problem of selecting all good from among $(\theta_{1,n+1}, \dots, \theta_{k,n+1})$ compared with the standard value θ_0 using the loss function $L(\underline{\theta}_{n+1}, \underline{a})$, where $\underline{\theta}_{n+1} = (\theta_{1,n+1}, \dots, \theta_{k,n+1})$. At stage $n + 1$, an empirical Bayes selection procedure, say $\delta_n = (\delta_{n1}, \dots, \delta_{nk})$, is a measurable function defined on the sample space of $\underline{Y} \times \underline{Y}(n)$, into the product space $[0, 1]^k$, so that $\delta_n(y, \underline{Y}(n)) \equiv (\delta_{n1}(y, \underline{Y}(n)), \dots, \delta_{nk}(y, \underline{Y}(n))) \equiv (\delta_{n1}(y), \dots, \delta_{nk}(y)) \equiv \delta_n(y)$ and $\delta_{ni}(y, \underline{Y}(n)) = \delta_{ni}(y)$ is the probability of selecting π_i as good.

Let $R(G, \delta_n | \underline{Y}(n))$ denote the conditional Bayes risk of the empirical Bayes selection procedure δ_n conditioning on $\underline{Y}(n)$, and let $R(G, \delta_n)$ denote the overall Bayes risk of the selection procedure δ_n . Then,

$$\begin{cases} R(G, \underline{\delta}_n | Y(n)) &= \sum_{i=1}^k R_i(G, \delta_{ni} | Y(n)) \\ R_i(G, \delta_{ni} | Y(n)) &= \int_Y \left[\prod_{\substack{j=1 \\ j \neq i}}^k f_j(y_j) \right] u(y_i) \delta_{ni}(y) H_i(y_i) dy + C_i \end{cases} \quad (3.1)$$

and

$$\begin{cases} R(G, \underline{\delta}_n) &= \sum_{i=1}^k R_i(G, \delta_{ni}) \\ R_i(G, \delta_{ni}) &= \int_Y \left[\prod_{\substack{j=1 \\ j \neq i}}^k f_j(y_j) \right] u(y_i) E_{Y(n)}[\delta_{ni}(y)] H_i(y_i) dy + C_i \end{cases} \quad (3.2)$$

where the expectation $E_{Y(n)}$ is taken with respect to the probability measure generated by $Y(n)$.

Since $\underline{\delta}_G$ is the Bayes selection procedure, $R_i(G, \delta_{ni} | Y(n)) - R_i(G, \delta_{Gi}) \geq 0$ for all $Y(n), n$ and each $i = 1, \dots, k$. Thus $R(G, \underline{\delta}_n) - R(G, \underline{\delta}_G) = \sum_{i=1}^k [R_i(G, \delta_{ni}) - R_i(G, \delta_{Gi})] \geq 0$ for all n . This nonnegative regret Bayes risk $D(G, \underline{\delta}_n) = R(G, \underline{\delta}_n) - R(G, \underline{\delta}_G)$ is used as a measure of performance of the empirical Bayes selection procedure $\underline{\delta}_n$.

Definition 3.1. A sequence of empirical Bayes selection procedures $\{\underline{\delta}_n\}_{n=1}^{\infty}$ is said to be asymptotically optimal relative to the prior distribution G if $R(G, \underline{\delta}_n) - R(G, \underline{\delta}_G) = o(1)$. $\{\underline{\delta}_n\}_{n=1}^{\infty}$ is said to be asymptotically optimal of order $\{\alpha_n\}_{n=1}^{\infty}$ relative to the prior distribution G if $R(G, \underline{\delta}_n) - R(G, \underline{\delta}_G) = O(\alpha_n)$ where $\{\alpha_n\}_{n=1}^{\infty}$ is a sequence of positive numbers such that $\lim_{n \rightarrow \infty} \alpha_n = 0$.

3.2. The Proposed Empirical Bayes Selection Procedure

We construct an empirical Bayes selection procedure by mimicking the behavior of the Bayes selection procedure $\underline{\delta}_G$ of (2.6).

Note that the functions $\psi_{ia}(y), a = 1, 2$, can be written as:

$$\begin{cases} \psi_{i1}(y) &= \int_{t=y}^{\infty} \psi_{io}(t) dt, \\ \psi_{i2}(y) &= \int_{t=y}^{\infty} t \psi_{io}(t) dt - y \psi_{i1}(y). \end{cases} \quad (3.3)$$

For each $i = 1, \dots, k, \ell = 1, 2, \dots$, and $y > 0$, define

$$V_{i\ell}(y) = I(Y_{i\ell} \geq y)/u(Y_{i\ell}). \quad (3.4)$$

Then, $E_{Y_{(n)}}[V_{i\ell}(y)] = \psi_{i1}(y)$, $E_{Y_{(n)}}[(Y_{i\ell} - y)V_{i\ell}(y)] = \psi_{i2}(y)$. Thus, for $W_{i\ell}(y) = (\theta_0 + y - Y_{i\ell})V_{i\ell}(y)$, $E_{Y_{(n)}}[W_{i\ell}(y)] = \theta_0\psi_{i1}(y) - \psi_{i2}(y) \equiv H_i(y)$. Now, for each $i = 1, \dots, k$, and $y > 0$, define

$$H_{in}(y) = \frac{1}{n} \sum_{\ell=1}^n W_{i\ell}(y) \quad (3.5)$$

$H_{in}(y)$ is an unbiased and consistent estimator of $H_i(y)$. By mimicking the form (2.6), we propose an empirical Bayes selection procedure $\delta_n^* = (\delta_{n1}^*, \dots, \delta_{nk}^*)$ as follows: For each $i = 1, \dots, k$, and $y_i > 0$,

$$\delta_{ni}^*(y_i) = \begin{cases} 1 & \text{if } H_{in}(y_i) \leq 0, \\ 0 & \text{otherwise.} \end{cases} \quad (3.6)$$

The Bayes risk of the empirical Bayes selection procedure δ_n^* is:

$$\begin{aligned} R(G, \delta_n^*) &= \sum_{i=1}^k R_i(G, \delta_{ni}^*), \\ R_i(G, \delta_{ni}^*) &= \int_{y=0}^{\infty} u(y) E_{Y_{(n)}}[\delta_{ni}^*(y)] H_i(y) dy + C_i \\ &= \int_{y=0}^{\infty} u(y) E_{Y_{(n)}}[\delta_{ni}^*(y)] \psi_{i1}(y) [\theta_0 - \varphi_i(y)] dy + C_i. \end{aligned} \quad (3.7)$$

4. Asymptotic Optimality and Rate of Convergence

4.1. Asymptotic Optimality of δ_n^*

From (2.8) and (3.7), the regret Bayes risk of the selection procedure δ_n^* is:

$$R(G, \delta_n^*) - R(G, \delta_G) = \sum_{i=1}^k [R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi})] \quad (4.1)$$

and from (2.9), for each $i = 1, \dots, k$.

$$\begin{aligned} &R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi}) \\ &= \int_{y=0}^{\infty} u(y) \psi_{i1}(y) [\theta_0 - \varphi_i(y)] E_{Y_{(n)}}[\delta_{ni}^*(y) - \delta_{Gi}(y)] dy \\ &= \int_{y=0}^{a_i} u(y) \psi_{i1}(y) [\theta_0 - \varphi_i(y)] P\{\delta_{ni}^*(y) = 1, \delta_{Gi}(y) = 0\} dy \\ &\quad + \int_{y=a_i}^{\infty} u(y) \psi_{i1}(y) [\varphi_i(y) - \theta_0] P\{\delta_{ni}^*(y) = 0, \delta_{Gi}(y) = 1\} dy. \end{aligned} \quad (4.2)$$

Note that under the assumption that $\int \theta^2 dG_i(\theta) < \infty$, we have

$$\begin{aligned} & \int_0^\infty u(y)\psi_{i1}(y)|\theta_0 - \varphi_i(y)|dy \\ & \leq \int_0^\infty \theta_0 u(y)\psi_{i1}(y)dy + \int_0^\infty u(y)\psi_{i1}(y)\varphi_i(y)dy \\ & = \theta_0 \int \theta dG_i(\theta) + \int \theta^2 dG_i(\theta) < \infty. \end{aligned}$$

Therefore, to establish the asymptotic optimality of the selection procedure δ_n^* , it suffices to show that for each $i = 1, \dots, k$, $P\{\delta_{ni}^*(y) = 1, \delta_{Gi}(y) = 0\} \rightarrow 0$ as $n \rightarrow \infty$ for each $0 < y < a_i$, and $P\{\delta_{ni}^*(y) = 0, \delta_{Gi}(y) = 1\} \rightarrow 0$ as $n \rightarrow \infty$ for each $y > a_i$.

In either case, for $\epsilon = 0, 1$, by (2.6), (3.6) and the definition of $H_{in}(y)$,

$$\begin{aligned} & P\{\delta_{ni}^*(y) = \epsilon, \delta_{Gi}(y) = 1 - \epsilon\} \\ & \leq P\{|H_{in}(y) - H_i(y)| > |H_i(y)|\} \\ & \leq \frac{E_{Y(n)}|H_{in}(y) - H_i(y)|^2}{[H_i(y)]^2} = \frac{1}{n[H_i(y)]^2} \text{Var}(W_{i\ell}(y)), \end{aligned}$$

which tends to 0 as $n \rightarrow \infty$ if $\text{Var}(W_{i\ell}(y))$ is finite.

Note that $W_{i\ell}(y) = (\theta_0 + y - Y_{i\ell})I(Y_{i\ell} \geq y)/Y_{i\ell}^{m-1}$. If $m \geq 2$, $W_{i\ell}(y)$ is a bounded random variable, and therefore, $\text{Var}(W_{i\ell}(y)) < \infty$. If $m = 1$, $V_{i\ell}(y) = I(Y_{i\ell} \geq y)$ and $\text{Var}(W_{i\ell}(y)) \leq 2(\theta_0 + y)^2 \text{Var}(V_{i\ell}(y)) + 2\text{Var}(Y_{i\ell}V_{i\ell}(y)) < \infty$ since $\text{Var}(V_{i\ell}(y)) \leq 1$ and $\text{Var}(Y_{i\ell}V_{i\ell}(y)) \leq E[Y_{i\ell}^2] = E[E[Y_{i\ell}^2|\Theta_i]] = E[2\Theta_i^2] < \infty$.

We summarize the result of the preceding discussion as a theorem as follows:

Theorem 4.1 Let δ_n^* be the empirical Bayes selection procedure constructed in Section 3. Suppose that $\int \theta^2 dG_i(\theta) < \infty$ for each $i = 1, \dots, k$. Then, δ_n^* is asymptotically optimal in the sense that $R(G, \delta_n^*) - R(G, \delta_G) = o(1)$.

4.2. Rate of Convergence

In this subsection, we investigate the rate of convergence of the empirical Bayes selection procedure δ_n^* by establishing an upper bound on the regret Bayes risk $R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi})$ for each $i = 1, \dots, k$. In the following, we consider the case where $m \geq 2$.

Therefore, $W_{i\ell}(y)$ is a bounded random variable, with

$$\begin{aligned}
\text{Var}(W_{i\ell}(y)) &\leq E[W_{i\ell}(y)]^2 \\
&\leq \int_y^\infty \frac{(t-y-\theta_0)^2}{u(t)} \psi_{i0}(t) dt \\
&\leq \frac{1}{u(y)} \int_y^\infty (t-y-\theta_0)^2 \psi_{i0}(t) dt \\
&\leq \frac{1}{u(y)} [\theta_0^2 \psi_{i1}(y) + 2\psi_{i3}(y)].
\end{aligned} \tag{4.3}$$

From (4.2) and by the definitions of δ_n^* and δ_{Gi} ,

$$\begin{aligned}
&R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi}) \\
&= \int_0^{a_i/2} u(y) \psi_{i1}(y) [\theta_0 - \varphi_i(y)] P\{H_{in}(y) - H_i(y) \leq -H_i(y)\} dy \\
&\quad + \int_{a_i/2}^{a_i} u(y) \psi_{i1}(y) [\theta_0 - \varphi_i(y)] P\{H_{in}(y) - H_i(y) \leq -H_i(y)\} dy \\
&\quad + \int_{a_i}^{a_i+1} u(y) \psi_{i1}(y) [\varphi_i(y) - \theta_0] P\{H_{in}(y) - H_i(y) \geq -H_i(y)\} dy \\
&\quad + \int_{a_i+1}^\infty u(y) \psi_{i1}(y) [\varphi_i(y) - \theta_0] P\{H_{in}(y) - H_i(y) \geq -H_i(y)\} dy \\
&\equiv D_{i1} + D_{i2} + D_{i3} + D_{i4}(\text{say}).
\end{aligned} \tag{4.4}$$

Note that for each $y \in [\frac{a_i}{2}, a_i]$, $0 \leq H_i(y) = \theta_0 \psi_{i1}(y) - \psi_{i2}(y) \leq \theta_0 \psi_{i1}(y) \leq \theta_0 \psi_{i1}(\frac{a_i}{2})$ since $\psi_{i1}(y)$ is decreasing in y for $y > 0$, and $W_{i\ell}(y)$, $\ell = 1, 2, \dots, n$, are iid, bounded random variables with

$$\begin{aligned}
|W_{i\ell}(y)| &= \left| \frac{(\theta_0 + y - Y_{i\ell}) I(Y_{i\ell} \geq y)}{Y_{i\ell}^{m-1}} \right| \leq \frac{\theta_0 I(Y_{i\ell} \geq y)}{Y_{i\ell}^{m-1}} + \frac{(Y_{i\ell} - y) I(Y_{i\ell} > y)}{Y_{i\ell}^{m-1}} \\
&\leq \frac{\theta_0}{(\frac{a_i}{2})^{m-1}} + \frac{1}{(\frac{a_i}{2})^{m-2}}.
\end{aligned}$$

So, there exists a number, say $Q_i(\theta_0) > 0$, such that $|W_{i\ell}(y) - H_i(y)| \leq \frac{Q_i(\theta_0)}{2}$ for all $y \in [a_i/2, a_i]$. Hence, by Hoeffding's inequality and the definition of $H_{in}(y)$, for each $y \in [a_i/2, a_i]$,

$$\begin{aligned}
P\{H_{in}(y) - H_i(y) \leq -H_i(y)\} &\leq \exp \left\{ \frac{-2nH_i^2(y)}{Q_i^2(\theta_0)} \right\} \\
&= \exp \left\{ \frac{-2n\psi_{i1}^2(y)[\theta_0 - \varphi_i(y)]^2}{Q_i^2(\theta_0)} \right\} \\
&\leq \exp\{-nb_i[\theta_0 - \varphi_i(y)]^2\},
\end{aligned} \tag{4.5}$$

where $b_i = 2\psi_{i1}^2(\frac{a_i}{2})/Q_i^2(\theta_0)$.

Let $c_i = u(a_i)\psi_{i1}(\frac{a_i}{2})$. Then $0 < u(y)\psi_{i1}(y) \leq u(a_i)\psi_{i1}(\frac{a_i}{2}) = c_i$ for all $y \in [\frac{a_i}{2}, a_i]$. Next for each $y \in [\frac{a_i}{2}, a_i]$, since G_i is non-degenerate.

$$\begin{aligned} \frac{-d}{dy}[\theta_0 - \varphi_i(y)] &= \frac{d}{dy} \frac{\psi_{i2}(y)}{\psi_{i1}(y)} \\ &= \frac{\int \theta^2 c(\theta) e^{-y/\theta} dG_i(\theta) \cdot \int c(\theta) e^{-y/\theta} dG_i(\theta) - [\int \theta c(\theta) e^{-y/\theta} dG_i(\theta)]^2}{\int \theta c(\theta) e^{-y/\theta} dG_i(\theta)} \\ &= \frac{\psi_{i2}(y)\psi_{i0}(y) - [\psi_{i1}(y)]^2}{[\psi_{i1}(y)]^2} \\ &\geq d_i(a_i) > 0. \end{aligned}$$

Therefore, combining the preceding inequalities and replacing them into D_{i2} , we obtain

$$\begin{aligned} D_{i2} &\leq \int_{a_i/2}^{a_i} c_i[\theta_0 - \varphi_i(y)] \exp\{-nb_i[\theta_0 - \varphi_i(y)]^2\} dy \\ &= \int_{a_i/2}^{a_i} \frac{c_i[-2nb_i(\theta_0 - \varphi_i(y))(\theta_0 - \varphi_i(y))']}{-2nb_i(\theta_0 - \varphi_i(y))^1} \exp\{-nb_i[\theta_0 - \varphi_i(y)]^2\} dy \\ &\leq \int_{a_i/2}^{a_i} \frac{c_i[-2nb_i(\theta_0 - \varphi_i(y))(\theta_0 - \varphi_i(y))']}{2nb_i d_i(a_i)} \exp(-nb_i[\theta_0 - \varphi_i(y)]^2) dy. \quad (4.6) \\ &= \frac{c_i}{2nb_i d_i(a_i)} \exp(-nb_i[\theta_0 - \varphi_i(y)]^2) \Big|_{y=\frac{a_i}{2}}^{a_i} \\ &\leq \frac{c_i}{2nb_i d_i(a_i)} \\ &= O(n^{-1}), \end{aligned}$$

where $(\theta_0 - \varphi_i(y))' = \frac{d}{dy}[\theta_0 - \varphi_i(y)]$.

Following an analogous argument, we obtain

$$D_{i3} = O(n^{-1}). \quad (4.7)$$

Next, for $0 < y \leq a_i/2$, by Markov's inequality,

$$\begin{aligned} P\{H_{in}(y) - H_i(y) \leq -H_i(y)\} &\leq \frac{E[H_{in}(y) - H_i(y)]^2}{[H_i(y)]^2} \\ &= \frac{\text{Var}(W_{i1}(y))}{n|H_i(y)|^2} \\ &\leq \frac{\theta_0^2 \psi_{i1}(y) + 2\psi_{i3}(y)}{n|H_i(y)|^2 u(y)} \end{aligned}$$

where the last inequality follows from (4.3).

Also, for $y \in (0, \frac{a_i}{2}]$, $\theta_0 - \varphi_i(y) \geq \theta_0 - \varphi_i(\frac{a_i}{2}) > 0$. Therefore,

$$\begin{aligned} D_{i1} &\leq \int_0^{a_i/2} \frac{1}{n[\theta_0 - \varphi_i(y)]\psi_{i1}(y)} [\theta_0^2 \psi_{i1}(y) + 2\psi_{i3}(y)] dy \\ &\leq \int_0^{a_i/2} \frac{\theta_0^2}{n[\theta_0 - \varphi_i(\frac{a_i}{2})]} dy + \int_0^{a_i/2} \frac{2}{n[\theta_0 - \varphi_i(\frac{a_i}{2})]} \times \frac{\psi_{i3}(y)}{\psi_{i1}(y)} dy. \end{aligned} \tag{4.8}$$

Here, we note that since $m \geq 2$,

$$\begin{aligned} 0 < \psi_{i3}(y) &= \int \theta^3 c(\theta) e^{-y/\theta} dG_i(\theta) \\ &= \int_{\theta=0}^1 \theta^3 c(\theta) e^{-y/\theta} dG_i(\theta) + \int_1^\infty \theta^3 c(\theta) e^{-y/\theta} dG_i(\theta) \\ &\leq \int_0^1 \theta c(\theta) e^{-y/\theta} dG_i(\theta) + \int_1^\infty \frac{\theta^2}{\Gamma(m)} e^{-y/\theta} dG_i(\theta) \\ &< \infty, \end{aligned}$$

and $\frac{\psi_{i3}(y)}{\psi_{i1}(y)}$ is increasing in y for $y > 0$. Hence, $\int_0^c \frac{\psi_{i3}(y)}{\psi_{i1}(y)} dy < \infty$ for every $c > 0$. Combining these results into (4.8), we obtain:

$$D_{i1} = O(n^{-1}). \tag{4.9}$$

For $y > a_i + 1$, by Markov's inequality, for $0 < \lambda \leq 2$,

$$P\{H_{in}(y) - H_i(y) \geq -H_i(y)\} \leq \frac{E[|H_{in}(y) - H_i(y)|^\lambda]}{|H_i(y)|^\lambda}.$$

Therefore,

$$\begin{aligned}
D_{i4} &\leq \int_{a_i+1}^{\infty} u(y)|H_i(y)|^{1-\lambda} E[|H_{in}(y) - H_i(y)|^\lambda] dy \\
&\leq \int_{a_i+1}^{\infty} u(y)|H_i(y)|^{1-\lambda} [E[H_{in}(y) - H_i(y)]^2]^{\lambda/2} dy \\
&= \int_{a_i+1}^{\infty} \frac{u(y)|H_i(y)|^{1-\lambda}}{n^{\lambda/2}} \text{Var}^{\lambda/2}(W_{i1}(y)) dy.
\end{aligned} \tag{4.10}$$

So far, the rates of order $O(n^{-1})$ regarding the three terms D_{i1} , D_{i2} and D_{i3} are obtained only based on the conditions that $\int \theta^2 dG_i(\theta) < \infty$ and Assumption A holds. Therefore D_{i4} is an essential part for the rate of convergence of $R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi})$. We summarize the preceding result as a theorem as follows.

Theorem 4.2. Suppose that Assumption A holds, $\int \theta^2 dG_i(\theta) < \infty$ for each $i = 1, 2, \dots, k$ and $\int_{a_i+1}^{\infty} u(y)|H_i(y)|^{1-\lambda} \text{Var}^{\lambda/2}(W_{i1}(y)) dy < \infty$, $i = 1, \dots, k$. Then, $R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi}) = O(n^{-\lambda/2})$ for each $i = 1, \dots, k$, and the empirical Bayes selection procedure $\hat{\delta}_n^*$ is asymptotically optimal of order $O(n^{-\lambda/2})$ for some $0 < \lambda \leq 2$. That is, $R(G, \hat{\delta}_n^*) - R(G, \hat{\delta}_G) = O(n^{-\lambda/2})$.

To see how the asymptotic behavior of D_{i4} is influenced by the tail probability of the probability density $f_i(y)$, we introduce the following lemma.

Lemma 4.1 Let X be a nonnegative random variable with probability density function $h(x)$. Then for $0 < t < 1$ and $p > \frac{1}{t}$, $\int_1^{\infty} h^t(x) dx \leq (pt - 1)^{t-1} [E_h[X^{p(1-t)}]]^t$.

Proof: Note that $q(x) = (pt - 1)x^{-pt}$ is a probability density on $(1, \infty)$. Now,

$$\begin{aligned}
\int_1^\infty h^t(x) dx &= \frac{1}{pt - 1} \int_1^\infty (pt - 1)x^{-pt} [x^p h(x)]^t dx \\
&= \frac{1}{pt - 1} E_q[X^p h(X)]^t \text{ where } E_q \text{ is taken wrt } q(x) \\
&\leq \frac{1}{pt - 1} (E_q[X^p h(X)])^t \text{ by Hölder inequality} \\
&= \frac{1}{pt - 1} \left(\int_1^\infty (pt - 1)x^{-pt} x^p h(x) dx \right)^t \\
&= (pt - 1)^{t-1} \left(\int_1^\infty x^{p(1-t)} h(x) dx \right)^t \\
&\leq (pt - 1)^{t-1} (E_h[X^{p(1-t)}])^t.
\end{aligned}$$

□

For $y \geq a_i + 1$, $\varphi_i(y) - \theta_0 \geq \varphi_i(a_i + 1) - \theta_0 \equiv e_i > 0$. Also, note that $u(y)\psi_{i1}(y) = m_1(G_i)f_i^*(y)$ where $f_i^*(y)$ is a probability density defined in (2.10). Hence, by (4.3),

$$\begin{aligned}
&\int_{a_i+1}^\infty u(y)|H_i(y)|^{\lambda-1} \text{Var}^{\lambda/2}(W_{i1}(y)) dy \\
&\leq \int_{a_i+1}^\infty \frac{u(y)\psi_{i1}^{1-\lambda}(y)}{|\varphi_i(y) - \theta_0|^{\lambda-1}} \times \frac{1}{u^{\lambda/2}(y)} [\theta_0^2 \psi_{i1}(y) + 2\psi_{i3}(y)]^{\lambda/2} dy \\
&\leq \int_{a_i+1}^\infty \frac{u^{1-\lambda/2}(y)\psi_{i1}^{1-\lambda}(y)}{e_i^{\lambda-1}} [(2\theta_0^2 \psi_{i1}(y))^{\lambda/2} + (4\psi_{i3}(y))^{\lambda/2}] dy \\
&= \frac{2^{\lambda/2} \theta_0^\lambda}{e_i^{\lambda-1}} \int_{a_i+1}^\infty [u(y)\psi_{i1}(y)]^{1-\lambda/2} dy \\
&\quad + \frac{2^\lambda}{e_i^{\lambda-1}} \int_{a_i+1}^\infty [u(y)\psi_{i1}(y)]^{1-\lambda/2} \left(\frac{\psi_{i3}(y)}{\psi_{i1}(y)} \right)^{\lambda/2} dy
\end{aligned}$$

$$\begin{aligned}
&= \frac{2^{\lambda/2} \theta_0^2 (m_1(G_i))^{1-\lambda/2}}{e_i^{\lambda-1}} \int_{a_i+1}^{\infty} f_i^{*1-\lambda/2}(y) dy \\
&\quad + \frac{2^{\lambda} (m_1(G_i))^{1-\lambda/2}}{e_i^{\lambda-1}} \int_{a_i+1}^{\infty} f_i^{*1-\lambda/2}(y) \left[\frac{\psi_{i3}(y)}{\psi_{i1}(y)} \right]^{\lambda/2} dy.
\end{aligned} \tag{4.11}$$

By Lemma 4.1,

$$\begin{aligned}
\int_{a_i+1}^{\infty} f_i^{*1-\lambda/2}(y) dy &\leq \int_1^{\infty} f_i^{*1-\lambda/2}(y) dy \\
&\leq (p(1-\lambda/2) - 1)^{-\lambda/2} (E_{f_i^*}[Y_i^{p\lambda/2}])^{1-\lambda/2},
\end{aligned} \tag{4.12}$$

for $p > \frac{1}{1-\lambda/2} = \frac{2}{2-\lambda}$, and where

$$\begin{aligned}
E_{f_i^*}[Y_i^{p\lambda/2}] &= \frac{E_{(G_i, f_i)}[\Theta_i Y_i^{p\lambda/2}]}{m_1(G_i)} \\
&= \frac{E_{G_i}[\Theta_i E_{f_i}[Y_i^{p\lambda/2} | \Theta_i]]}{m_1(G_i)} \\
&= \frac{\Gamma(m + p\lambda/2)}{\Gamma(m) m_1(G_i)} E_{G_i}[\Theta_i^{p\lambda/2+1}].
\end{aligned} \tag{4.13}$$

Therefore,

$$\begin{aligned}
&\int_{a_i+1}^{\infty} f_i^{*1-\lambda/2}(y) dy \\
&\leq (p(1-\lambda/2) - 1)^{-\lambda/2} \times \left[\frac{\Gamma(m + p\lambda/2)}{\Gamma(m) m_1(G_i)} \right]^{1-\lambda/2} \times [E_{G_i}(\Theta_i^{p\lambda/2+1})]^{1-\lambda/2}.
\end{aligned} \tag{4.14}$$

Also, by Hölder inequality, for $s > 1$ such that $\lambda s < 2$ and $\frac{\lambda}{2} \times \frac{s}{s-1} \geq 1$,

$$\begin{aligned}
&\int_{a_i+1}^{\infty} f_i^{*1-\lambda/2}(y) \left[\frac{\psi_{i3}(y)}{\psi_{i1}(y)} \right]^{\lambda/2} dy \\
&= E_{f_i^*} \left[f_i^{*1-\lambda/2}(Y) I(Y \geq a_i + 1) \left[\frac{\psi_{i3}(Y)}{\psi_{i1}(Y)} \right]^{\lambda/2} \right] \\
&\leq [E_{f_i^*}[f_i^*(Y) I(Y \geq a_i + 1)]^{-\lambda s/2}]^{1/s} \times \left[E_{f_i^*} \left[\frac{\psi_{i3}(Y)}{\psi_{i1}(Y)} \right]^{\frac{\lambda}{2} \cdot \frac{s}{s-1}} \right]^{\frac{s-1}{s}},
\end{aligned} \tag{4.15}$$

where

$$\begin{aligned}
& E_{f_i^*} [f_i^*(Y) I(Y \geq a_i + 1)]^{-\lambda s/2} \\
&= \int_{a_i+1}^{\infty} f_i^{*1-\lambda s/2}(y) dy \\
&\leq (p(1 - \lambda s/2) - 1)^{-\lambda s/2} \left[\frac{\Gamma(m + p\lambda s/2)}{\Gamma(m)m_1(G_i)} \right]^{1-\lambda s/2} \times [E_{G_i}(\Theta_i^{ps\lambda/2+1})]^{1-\lambda s/2},
\end{aligned} \tag{4.16}$$

for $p > \frac{1}{1-\frac{\lambda s}{2}} = \frac{2}{2-\lambda s}$.

Since $\frac{\psi_{i3}(y)}{\psi_{i1}(y)} = E_{G_i^*}[\Theta_i^2 | Y_i = y]$ and $\frac{\lambda}{2} \times \frac{s}{s-1} \geq 1$

$$\begin{aligned}
E_{f_i^*} \left[\frac{\psi_{i3}(y)}{\psi_{i1}(Y)} \right]^{\frac{\lambda}{2} \times \frac{s}{s-1}} &= E_{f_i^*} [E_{G_i^*}[\Theta_i^2 | Y_i]]^{\frac{\lambda}{2} \times \frac{s}{s-1}} \\
&\leq E_{f_i^*} E_{G_i^*} [\Theta_i^{\frac{\lambda s}{s-1}} | Y_i] \\
&= E_{G_i^*} [\Theta_i^{\frac{\lambda s}{s-1}}] \\
&= E_{G_i} [\Theta_i^{\frac{\lambda s}{s-1}+1}] / m_1(G_i).
\end{aligned} \tag{4.17}$$

For the two moments $E_{G_i}[\Theta_i^{\frac{ps\lambda}{2}+1}]$ and $E_{G_i}[\Theta_i^{\frac{\lambda s}{s-1}+1}]$ with parameters p, s and λ such that $1 < \lambda < 2$, $s > 1$, $\lambda s < 2$, $\frac{\lambda s}{2(s-1)} \geq 1$ and $p > \frac{1}{1-\frac{\lambda s}{2}} = \frac{2}{2-\lambda s}$, they will be equal if we let $\frac{ps\lambda}{2} = \frac{\lambda s}{s-1}$, which implies that $p = \frac{2}{s-1}$. Also, $p = \frac{2}{s-1} > \frac{2}{2-\lambda s} \Rightarrow 1 < s < \frac{3}{1+\lambda}$.

We summarize the results of the preceding discussion as a Corollary of Theorem 4.2 as follows.

Corollary 4.1. Suppose that Assumption A holds and for each $i = 1, \dots, k$, $\int \theta^{\frac{\lambda s}{s-1}+1} dG_i(\theta) < \infty$ for some $1 < \lambda < 2$, $s > 1$, such that $\lambda s < 2$, $\frac{\lambda s}{2(s-1)} \geq 1$ and $s < \frac{3}{1+\lambda}$. Then,

- (a) $\int_{a_i+1}^{\infty} u(y) |H_i(y)|^{1-\lambda} \text{Var}^{\lambda/2}(W_{i1}(y)) dy < \infty$ for each $i = 1, \dots, k$.
- (b) The empirical Bayes selection procedure δ_n^* is asymptotically optimal of order $O(n^{-\lambda/2})$.

5. A Lower Bound for $R(G, \delta_n^*) - R(G, \delta_G)$ and the Best Possible Rate of Convergence

In this section, we will establish a lower bound with its rate of convergence for the regret Bayes risk $R(G, \delta_n^*) - R(G, \delta_G)$. In fact, it suffices to consider a lower bound, say, for $R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi})$ since $R(G, \delta_n^*) - R(G, \delta_G) \geq R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi})$.

Theorem 5.1. Let Assumption A hold. Then,

$$R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi}) \geq O(n^{-1}).$$

Proof: From (4.4)

$$\begin{aligned} & R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi}) \\ & \geq \int_{\frac{a_i}{2}}^{a_i} u(y) \psi_{i1}(y) [\theta_0 - \varphi_i(y)] P\{H_{in}(y) - H_i(y) \leq -H_i(y)\} dy. \end{aligned} \quad (5.1)$$

It follows from Lemma 3, on page 47, of Lamperti (1966) that for all $\xi > 0$, and for n being sufficiently large,

$$\begin{aligned} & P\{H_{in}(y) - H_i(y) \leq -H_i(y)\} \\ & = P\left\{ \frac{\sqrt{n}(H_{in}(y) - H_i(y))}{\sqrt{\text{Var}(W_{i1}(y))}} \leq \frac{-\sqrt{n}H_i(y)}{\sqrt{\text{Var}(W_{i1}(y))}} \right\} \\ & \geq \exp\left\{ -\frac{nH_i^2(y)(1+\xi)}{2 \text{Var}(W_{i1}(y))} \right\} \\ & = \exp\left\{ -\frac{n\psi_{i1}^2(y)(1+\xi)(\theta_0 - \varphi_i(y))^2}{2 \text{Var}(W_{i1}(y))} \right\} \\ & \geq \exp\left\{ -\frac{n\psi_{i1}^2(\frac{a_i}{2})(1+\xi)(\theta_0 - \varphi_i(y))^2}{\gamma_i} \right\} \\ & = \exp\{-n\tau_{i1}(\theta_0 - \varphi_i(y))^2\}, \end{aligned} \quad (5.2)$$

where $\gamma_i = 2 \min_{\frac{a_i}{2} \leq y \leq a_i} \text{Var}(W_{i1}(y)) > 0$ Since G_i is non-degenerate under Assumption A and

$[\frac{a_i}{2}, a_i]$ is a compact interval, and $\tau_{i1} = \psi_{i1}^2(\frac{a_i}{2})(1+\xi)/\gamma_i > 0$. Let $\tau_{i2} = \min_{\frac{a_i}{2} \leq y \leq a_i} \frac{u(y)\psi_{i1}(y)}{\varphi_i'(y)}$.

Then $\tau_{i2} > 0$. Therefore, from (5.1) and (5.2),

$$\begin{aligned} & R_i(G, \delta_{ni}^*) - R_i(G, \delta_{Gi}) \\ & \geq \int_{\frac{a_i}{2}}^{a_i} u(y) \psi_{i1}(y) [\theta_0 - \varphi_i(y)] \exp\{-n\tau_{i1}(\theta_0 - \varphi_i(y))^2\} dy \\ & = \int_{\frac{a_i}{2}}^{a_i} \frac{u(y) \psi_{i1}(y) 2n\tau_{i1}(\theta_0 - \varphi_i(y)) \varphi_i'(y)}{2n\tau_{i1} \varphi_i'(y)} \exp\{-n\tau_{i1}(\theta_0 - \varphi_i(y))^2\} dy \end{aligned}$$

$$\begin{aligned}
&\geq \int_{a_i/2}^{a_i} \frac{\tau_{i2}}{2n\tau_{i1}} 2n\tau_{i1}(\theta_0 - \varphi_i(y))\varphi_i'(y) \exp\{-n\tau_{i1}(\theta_0 - \varphi_i(y))^2\} dy \\
&= \frac{\tau_{i2}}{2n\tau_{i1}} \exp\{-n\tau_{i1}(\theta_0 - \varphi_i(y))^2\} \Big|_{y=a_i/2}^{a_i} \\
&= \frac{\tau_{i2}}{2n\tau_{i1}} [1 - \exp\{-n\tau_{i1}(\theta_0 - \varphi_i(a_i/2))^2\}] \\
&= O(n^{-1}).
\end{aligned} \tag{5.3}$$

Therefore, the proof is complete. \square

Theorem 5.1 provides a lower bound with a rate of convergence of order $O(n^{-1})$ for the regret Bayes risk $R(G, \delta_n^*) - R(G, \delta_G)$, while Corollary 4.1 gives an upper bound with a rate of convergence of order $O(n^{-\lambda/2})$ for the regret Bayes risk. When λ is close to 2, a rate of convergence of order $O(n^{-1})$ will be the best possible rate of convergence for the empirical Bayes selection procedure δ_n^* . Suppose that the unknown prior distribution G is such that $G_i(\theta^*) = 1$ for some $0 < \theta^* < \infty, i = 1, \dots, k$, and Assumption A holds. Then $E_{G_i}[\Theta_i^t] < \infty$ for all $t > 0$. Thus, the quantity λ in Corollary 4.1 can be chosen to be very close to 2. For example, if we let $\lambda = \lambda_n = 2 - 2 \ln \ln n / \ln n$ for $n \geq 16$, then the rate of convergence is of order $O(n^{-1} \ln \ln n)$, which is close to $O(n^{-1})$.

6. Concluding Remarks

We have presented a method to construct an empirical Bayes procedures δ_n^* for selecting good exponential populations compared with a control. Through the analysis developed in Section 4, we can see that the part D_{i4} plays an essential role in determining the rate of convergence of the selection procedure δ_n^* . We have demonstrated that the rate of convergence of δ_n^* is influenced by the tail probability of the marginal probability densities $f_i(y), i = 1, \dots, k$, or the moments of the prior distribution G . This empirical Bayes selection procedure δ_n^* is asymptotically optimal and achieves a rate of convergence with order $O(n^{-\lambda/2}), 0 < \lambda \leq 2$, which may be close to the best possible rate of order $O(n^{-1})$ under some regularity conditions about the moments of G according to Corollary 4.1. When the random parameters $\Theta_{i\gamma}$ are bounded and Assumption A holds, we have exhibited that δ_n^* may achieve a rate of order $O(n^{-1} \ln \ln n)$, which is close to $O(n^{-1})$. However, it is not known whether δ_n^* achieves the rate of order $O(n^{-1})$ or not. Singh (1979) and

Singh and Wei (1992) have commented that “a rate of the order $O(n^{-1})$ has not been achieved for any empirical Bayes procedures, whatever may be the component problem, in any Lebesgue-exponential, non-exponential regular or irregular family”.

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This paper deals with empirical Bayes selection procedures for selecting good exponential populations compared with a control. Based on the accumulated historical data, an empirical Bayes selection procedure δ_n^* is constructed by mimicking the behavior of a Bayes selection procedure. The empirical Bayes selection procedure δ_n^* is proved to be asymptotically optimal. The analysis shows that the rate of convergence of δ_n^* is influenced by the tail probabilities of the underlying distributions. It is shown that under certain regularity conditions on the moments of the prior distribution, the empirical Bayes selection procedure δ_n^* is asymptotically optimal of order $O(n^{-\lambda/2})$ for some $0 < \lambda \leq 2$. A lower bound with rate of convergence of order $O(n^{-1})$ is also established for the regret Bayes risk of the empirical Bayes selection procedure δ_n^* . This result suggests that a rate of order $O(n^{-1})$ might be the best possible rate of convergence for this empirical Bayes selection problem.

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